# MEASURING BRAIN STATES OF CURIOSITY THROUGH ELECTROENCEPHALOGRAPHY SIGNALS

by

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**Abstract**

Epistemic curiosity, a desire to obtain knowledge, has been consistently associated with learning, such that information that is viewed as valuable is more likely to be remembered (e.g., Gruber et al., 2014; Kang et al., 2009). Prior studies have typically measured curiosity using self-report. However, physiological indices such as EEG activity could potentially act as a more reliable method and a complement to self-report. The present study aims to determine whether an objective measure of a state of curiosity can be obtained through the use of EEG methods and, additionally, provide further support for the relationship between curiosity and learning. Participants were presented with curiosity-inducing trivia questions (Fastrich et al., 2018) and provided ratings of curiosity, confidence, and prior knowledge. The answer to each question was shown, and participants rated their levels of satisfaction with the answer and accuracy on prior knowledge. EEG data were continuously recorded throughout the task. Participants then completed a recall test on the questions they had previously seen. Metrics such as frontal brain asymmetry, relative percentages of activity in each frequency band, and the average theta/beta ratio were examined using spectral analysis. Results provide further insight into the neural and psychological correlates of a curiosity state.



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# Measuring Brain States of Curiosity Through Electroencephalography Signals

Curiosity plays a key role in how we view and interact with the world around us. It drives many of our day-to-day behaviors, helps motivate us to learn new things, and is influential in decision-making processes. Psychologist William James (1899, p. 37) once described curiosity as “the impulse towards better cognition,” which implies that it is an intrinsic desire to acquire knowledge, which ultimately works to benefit an individual’s skill or mindset. Although curiosity is viewed as a basic yet fundamental aspect of our nature, it had not been widely researched in experimental psychology or cognitive neuroscience until relatively recently. Therefore, there is still much to learn regarding the psychological and neural underpinnings of curiosity and how they relate to other aspects of cognition.

## Types of Curiosity

In order to talk about curiosity in a constructive manner, it is necessary to differentiate between the various types. Berlyne (1954) categorized curiosity into two dimensions: perceptual and epistemic. Perceptual curiosity refers to exploratory behavior that leads to increased perception of stimuli in the environment, while epistemic curiosity is the drive for knowledge. For example, perceptual curiosity can arise in the presence of a novel or ambiguous stimulus in the environment about which an individual is uncertain. In a similar sense, epistemic curiosity arises when an individual is aware of information they are lacking, of which they are motivated to learn. An important distinction between these two types of curiosity is that epistemic curiosity mainly applies to human populations (Berlyne, 1954). Contemporary researchers typically define epistemic curiosity as an internally motivated state that encourages information seeking to reduce uncertainty regarding events, situations, or processes in which we have a personal interest (Kidd & Hayden, 2015). In the current study, I will focus on epistemic curiosity.

## Theories of Curiosity

Early theories of curiosity attempted to define the balance between states of aversiveness and states of pleasure when trying to make sense of unexpected stimuli in the environment (for a review, see Gruber et al., 2019). The optimal arousal theory (Berlyne, 1967) proposed that an optimal level of incongruity exists, such that slight violations of expectation result in a pleasurable state of curiosity, but larger violations instill a fear-like state. This account maintained that moderate levels of curiosity are the most pleasurable and thus are pursued more frequently compared to lower and higher levels of curiosity. However, this theory fails to explain why individuals tend to resolve their curiosity, since it had been believed that such pleasurable levels of curiosity were preferred (Gruber et al., 2019). Therefore, contemporary theories have strived to better explain the reasoning behind why individuals actively seek out resolutions to their curiosity.

### *Information Gap Theory of Curiosity*

The idea that curiosity may be characterized as a gap in knowledge, and therefore leads to a desire to fill that gap, was first generated by Loewenstein (1994). The information gap theory of curiosity asserts that curiosity results from a perceived gap between what one knows and what one would like to know. When a discrepancy is identified between these two states of knowledge, curiosity is elicited, and a drive to pursue information in order to satisfy our desire for knowledge occurs. The information gap theory also assumes that the level of desired knowledge sharply increases with a small gain in knowledge, such that initial learning coincides with growth in the information gap. In other words, just a small sample of information regarding a subject or topic without an idea of the bigger picture will tend to increase curiosity and the drive for knowledge (Loewenstein, 1994). However, once sufficient knowledge has been acquired, the information gap shrinks, therefore leading to a decrease in levels of curiosity. Since individuals feel compelled to fill these information gaps, curiosity can act as a driving force behind acquiring new knowledge.

Loewenstein’s theory is supported by research conducted by Kang and colleagues (2009), who found that curiosity piqued by trivia questions follows an upside-down U-shaped function of confidence in knowing the answer. In other words, individuals were the least curious when they had no idea what the answer could be and when they were extremely certain of the answer. The circumstance under which individuals were most curious was when they had a slight idea of what the answer might be, and their confidence was mid-range. Therefore, obtaining knowledge can be viewed as rewarding up until a threshold is reached at which enough new information has been acquired to satisfy the curiosity drive.

### ***Information-as-Reward Theory of Curiosity***

Similar to the previous theory, curiosity can be reframed to signify the motivation to obtain a reward: that of novel information. The information-as-reward framework, developed by Marvin and Shohamy (2016), allows for curiosity to be studied alongside other reward-motivated behaviors and seeks to describe the subjective value of those rewards. In fact, previous studies have demonstrated a similarity in behavioral and neurobiological properties between curiosity and basic reward-motivated behaviors. For instance, Bromberg-Martin and Hikosaka (2009) investigated the neural bases of physical rewards (i.e., water) versus cognitive rewards (i.e., information). Their study was based on the idea that both humans and animals often prefer to receive advance information about future rewards, even when the outcome cannot be influenced. Researchers utilized a simple decision task that required monkeys to choose whether they wanted to receive advance information regarding the size of an upcoming water reward. Results showed that the monkeys preferred advance information to its absence and to receive it as soon as possible. Furthermore, Bromberg-Martin and Hikosaka (2009) found that the same midbrain dopaminergic neurons (i.e., those that make up the substantia nigra and ventral tegmental area) that signal expectations of the water reward also signal expectations of advance information. This finding suggests that physical and cognitive rewards share similar neural bases and provides support for the idea that information can be viewed as rewarding.

Research using humans has also demonstrated that curiosity has similar neurobiological properties as reward anticipation. Kang and colleagues (2009) utilized fMRI to determine regions of brain activation while participants read trivia questions. They found that ratings of higher curiosity were associated with activation in brain areas that are known to respond to reward, such as the caudate and lateral prefrontal cortex. These results indicate that, when in a state of curiosity, people tend to anticipate information comparably to how they would anticipate a primary reward such as food. A separate behavioral study was conducted by Kang and colleagues (2009) to rule out the possibility that activation in the previously mentioned brain regions was due to attentiveness rather than reward anticipation. In line with the reward anticipation hypothesis, participants were more willing to spend resources (tokens or time) to find out the answers to questions that provoked higher levels of curiosity. Similarities in neural and behavioral responses to previously established measures of reward help support the framework that curiosity should be treated and studied as a type of reward-motivated behavior. When combining and applying the information-as-reward and information-gap approaches to curiosity, the main driving force that encourages us to enter this motivational state is receiving currently unknown information that is anticipated to be rewarding.

**Curiosity and Learning**

Curiosity has the potential to improve cognitive operations in a number of areas. One specific place in which curiosity may have a positive effect is in learning new information. A strong association exists between information that is viewed as valuable and the likelihood of remembering that information. For example, Gruber et al. (2014) conducted a study to determine the mechanisms through which intrinsic motivational states affect learning. In their study, participants rated their curiosity to learn the answers to a series of trivia questions and were then scanned using fMRI while viewing the answers along with a set of neutral, unrelated face stimuli. The face stimuli were encoded incidentally during the anticipatory phase before the participants were presented with the answer to each question. Afterwards, participants underwent a memory test for the faces and answers they previously saw. Gruber and colleagues (2014) found that participants recalled more answers to high curiosity questions compared to low curiosity questions. They also concluded that curiosity benefits learning of trivia questions via increased activation of the nucleus accumbens and hippocampus. More specifically, question-evoked activation in these regions predicted later memory performance but only for those answers associated with high ratings of curiosity. Furthermore, memory for faces that were incidentally encoded during a state of high curiosity was enhanced compared to those encoded during a state of low curiosity. These results indicate that curiosity-driven learning benefits are related to an anticipatory state that occurs before the unknown information is provided. Therefore, it can be inferred that it is a brain state of curiosity that is promoting learning, rather than the actual encoding of new information.

In addition to the finding that high-curiosity information enhances memory, gaps of information, often known as information prediction errors, may modulate the strength of the relationship between curiosity and memory. Neurobiological research has provided support for this theory, indicating that dopamine neurons in the midbrain signal the difference between the expected value of a reward and the actual value of a received reward. This phenomenon has been coined “reward prediction error,” as the dopamine neurons show enhanced activation when the reward is larger than expected, remain at baseline when rewards occur as expected, and show decreased activation when the reward is smaller than expected (Schultz, 2016). These findings implicate the importance of a prediction error-driven learning mechanism in the reward system. In sum, perhaps the discrepancy between the reward that is received versus the reward that was anticipated is a major driving force behind learning.

Marvin and Shohamy (2016) investigated information prediction errors in the context of curiosity and learning, defining it as the difference between the satisfaction experienced upon receiving information and the curiosity experienced in anticipation of the information. In their study, Marvin and Shohamy (2016) used a trivia question paradigm with willingness to wait as a measure of reward-motivated behavior. Participants were presented with a trivia question and were then instructed to select one of three options: *Skip*, *Know*, or *Wait*. The *Wait* option had a designated amount of time associated with it, such that participants had to wait that certain amount of time before they could see the answer to the question (between 10 and 30 seconds). Participants were instructed to select the *Know* option if they already knew the answer to the question and the *Skip* option if they did not know the answer but were not interested in finding out the answer or waiting the designated amount of time to find out. Only by selecting the *Wait* option would participants actually see the answer to the trivia question; they were instructed to do so if they were interested in finding out the answer and were willing to wait the designated amount of time beforehand. After the trivia task, participants were asked to rate their curiosity upon initially seeing each question and how satisfied they were with the answer. Marvin and

Shohamy (2016) found that, overall, participants were more likely to wait for information they were curious about, which supports the idea that willingness to wait can act as an objective measure of curiosity. In addition, participants were more likely to remember information that was associated with a more-positive prediction error—information for which satisfaction was greater than curiosity. These results indicate that the gap between expected and received reward, the prediction error, is a key player in driving learning and enhancing memory.

In the previously mentioned studies, curiosity had been measured using self-report. Since individual differences in inclinations to be curious are likely prevalent, it may be difficult to compare individuals' personal ratings across scales. While the self-report method is useful in understanding people's subjective feelings of curiosity, there may be benefit in obtaining a more objective measure of a state of curiosity as well. To achieve this, physiological indices can be used as a complement to self-report in order to produce more consistency in measurement. One such possible avenue is to measure electrical activity in the cortex through the use of EEG methods. Objective measures of curiosity have been previously established by studies utilizing fMRI; however, EEG can provide other advantageous insights about brain function that fMRI cannot. For example, EEG technology is able to detect changes in brain activity at the millisecond timescale and therefore has a much higher temporal resolution than fMRI technology. In addition, EEG is far more accessible to labs that are investigating curiosity or including aspects of curiosity in their research.

**EEG Frequency Components**

EEG methods can be utilized to study the neural correlates of various cognitive states, potentially including a state of curiosity. EEG waves recorded from the surface of the scalp represent the summation of post-synaptic potentials occurring synchronously in tens of thousands of neurons located in the cortex beneath a recording electrode (Cohen, 2014). An EEG waveform is a complex signal in which every frequency is present to at least some degree. Spectral analysis, based on principles developed by the French mathematician Jean Fourier in the early 1800s, specifies the variance (spectral power) captured by each frequency that could be contributing to a complex waveform. These values for spectral power can be summed within a range of frequencies to yield a percentage of the total variance in the waveform that is associated with that frequency range or band. EEG activity is frequently characterized through the use of the following frequency bands: delta (1-3 Hz), theta (3-8 Hz), alpha (8-12 Hz), and beta (12-40 Hz). A sample EEG record displaying dominant frequencies falling within each of these frequency bands is presented in Figure 1.

In order to quantify these patterns, a spectral analysis is commonly performed to determine the relative strengths of each periodic signal component (Williams, 1997). In other words, spectral analysis describes the percentages of brain activity that occur in each frequency band. The numerical value assigned to each frequency band reflects the percentage of area under the spectral curve that falls within the range of each band. Research regarding EEG correlates of cognitive function has been conducted using values assigned to specific frequency bands and to measures combining information in two or more frequency bands. A sample EEG frequency spectrum displaying its division into frequency bands is presented in Figure 2 below.

**Figure 1**

*EEG Tracings of Frequency Bands*

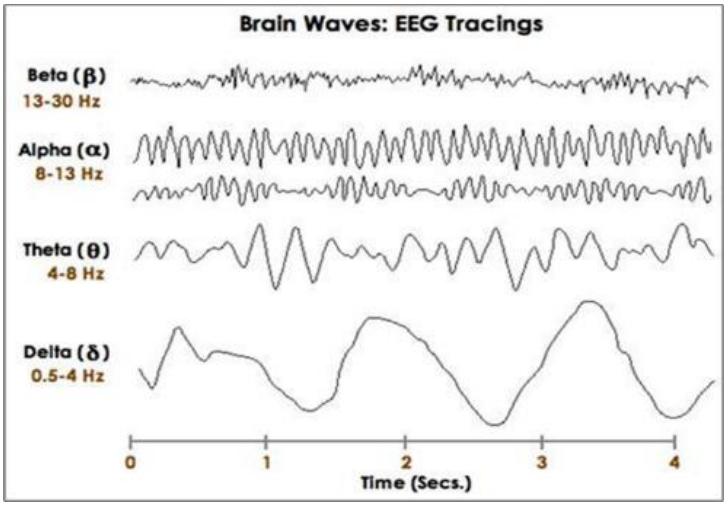
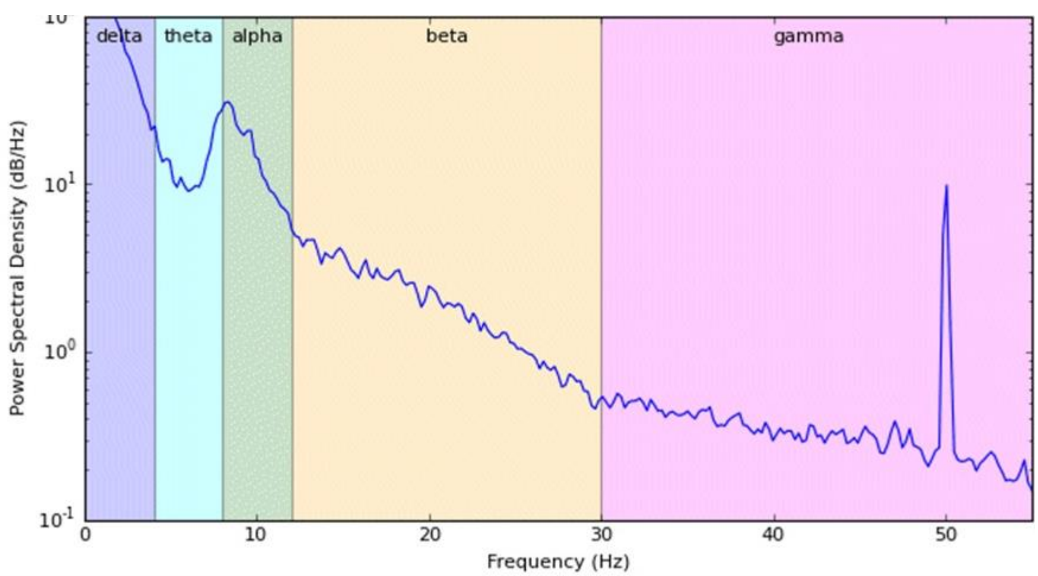



**Figure 2**

*Spectral Density Curve*




*Note.* This graph shows the spectral power associated with different values on the frequency spectrum. The value for power spectral density represents the amount of variance that is accounted for by the associated frequency.

### *Beta Frequency Band*

Using this technique of breaking down frequency components, EEG activity has been shown to be correlated with various cognitive states, such as attention. For example, higher frequency EEG waves, specifically activity that falls in the beta frequency band (13-18 Hz), are typically associated with states of concentration or cognitive effort (Smith et al., 2003). To extend this finding, Nguyen and Zeng (2017) investigated the relationship between subjective ratings of mental effort and EEG beta power. Participants were presented with a design problem, they generated a solution, and were instructed to rate their cognitive workload. Researchers found a significant association between self-reported mental effort and EEG-indicated effort, as defined by beta power. In other words, when individuals felt they were expending more cognitive effort on the design tasks, more high frequency beta waves were present in the EEG record. This indicates that a brain state of concentration can be characterized physiologically by the presence of beta waves. In order to extrapolate these findings to a curiosity brain state, we can think of epistemic curiosity as resulting in concentration or mental effort, perhaps from attempting to figure out or think about the unknown information. If it is the case that curiosity results in higher levels of concentration, we can assume that when an individual is in a state of curiosity, the EEG record will also show increased activity within the beta frequency band.

### *Alpha Frequency Band*

One of the initial and well-known hypotheses regarding the role of alpha power is that higher levels of alpha power reflect a low cortical arousal state, otherwise known as cortical idling, which is commonly associated with a decline in attention (Klimesch, 1999). However, other studies have observed that increases in alpha power may reflect a state of internally oriented attention. For example, Benedek and colleagues (2011) investigated whether alpha synchronization is related to internal processing demands by looking at the specific cognitive processes involved in creative thinking. To do this, participants completed both a convergent (asked to find anagram solution) and divergent task (asked to create an original sentence using given characters). Both tasks were presented in two experimental conditions: low internal processing and high internal processing. In the low internal processing condition, the stimuli were kept visible on the screen, so they could be processed in a bottom-up manner. Alternatively, the high internal processing condition included a stimulus mask after encoding so that the problem had to be solved without further bottom-up processing. Benedek et al. (2011) found that frontal alpha synchronization was present during both convergent and divergent thinking, but only when there was top-down control (i.e., during the high internal processing). Based on these results, it is possible that internally driven attention, such as imagining or brainstorming the answer to a trivia question, may result in higher alpha activity. Perhaps the more curious an individual is about the answer to a question, the more likely they are to engage in such internal processing about what the answer may be. However, more research is needed to further explore the relationship between alpha power and a state of attentional control.

### *Theta/Beta Ratio*

Another metric of EEG frequency components that has been widely researched is the theta/beta ratio, which is the percentage of activity in the theta band divided by the percentage of activity in the beta band. Prior work has shown that this ratio between low and high frequency power is related to attentional control. For example, dysregulated attentional control functions, as typically seen in attention-deficit/hyperactivity disorder (ADHD), have been routinely related to an increased theta/beta ratio (Barry et al., 2003). Therefore, it can be implied that a state of regulated attentional control is associated with a lower percentage of theta power compared to beta power, resulting in a decreased theta/beta ratio. Furthermore, van Son and colleagues (2019) investigated the relationship between the theta/beta ratio and levels of cognitive control via mind wandering, which occurs when thoughts are not controlled. In this study, participants took part in a breath-counting task, in which they were instructed to count their breath cycles repeatedly. As a measure of mind wandering, participants were also instructed to press a button whenever they realized that they had stopped counting. Researchers found that the frontal theta/beta ratio was increased during mind wandering compared to focused and controlled thought, which provides further support for its involvement in executive control processes (van Son et al., 2019).

Perhaps more closely relating the theta/beta ratio to a state of curiosity is a study that investigated the theta/beta ratio and sensitivity to reward and punishment (Massar et al., 2014). In this study, participants performed the Iowa Gambling Task, which required them to maximize their winnings while choosing from a set of cards that unpredictably yield either wins or losses. Both advantageous (frequent low gains and infrequent low losses leading to net gain) and disadvantageous (frequent high gains and infrequent higher losses) decks were present during the task. Massar and colleagues (2014) found that individuals with a higher theta/beta ratio learned to use the advantageous decks more slowly than those with a lower theta/beta ratio. This finding suggests that an increased theta/beta ratio may be associated with risk-taking behaviors and also implies that this measure is associated with activity in reward-related brain circuits.

Taken together, these findings indicate that the theta/beta ratio is related to a variety of cognitive functions that require prefrontal regulation of attentional and motivational processes. Since curiosity includes aspects of both of the above processes, it may be possible that the theta/beta ratio can provide further insight into defining an objective measure of a brain state of curiosity.

**Frontal Brain Asymmetry as a Measure of Motivation and Engagement**

Using the information-as-reward framework allows us to define curiosity as a state of motivation, which can then be investigated further based on preexisting knowledge regarding neural properties of related behavior. Frontal brain asymmetry (FBA) is a frequency-based metric that is typically used to measure engagement and motivation in electrodes over frontal cortical regions (Lima & Rocha, 2019). Previous studies have found that greater activity in the left compared to the right frontal cortex is associated with higher engagement, as well as greater approach motivation responses (Harmon-Jones & Gable, 2018). Therefore, one would expect that frontal brain asymmetry has the ability to indicate levels of curiosity and potentially even modulate the probability of taking part in reward-motivated behavior.

In fact, Lima and Rocha (2019) did investigate the neural correlates of curiosity using frontal brain asymmetry metrics of the alpha band and its effects on learning. Participants were presented with a series of trivia questions, instructed to type their answer, and then they indicated their curiosity about the correct answer. Each question was presented again along with the correct answer, and EEG data were recorded continuously throughout the whole task. After a one-week period, participants returned and were asked to write down the answer to each trivia question they had seen during the initial task. The frontal brain asymmetry index for each participant was calculated by taking the natural log of the alpha power level from the right frontal electrode divided by the value from the left frontal electrode. Alpha power is inversely related to brain activity, so a positive FBA score represents greater alpha, or less activity, over the right than left hemispheres (Coan & Allen, 2004). In other words, higher FBA scores corresponded with greater activity in the left compared to the right frontal regions, an indicator of higher engagement and motivation. Lima and Rocha (2019) found that participants' recall was better for trials in which they had higher FBA scores than those in which they had lower FBA scores, which suggests that frontal brain asymmetry predicts memory recall and certain aspects of learning. However, self-reported curiosity levels were not linked to higher FBA values.

Despite the lack of correlation between FBA and self-reported curiosity in Lima and Rocha's study, perhaps investigating frontal asymmetry in a different frequency band may provide insight into whether a brain state of curiosity can be physiologically measured. A majority of the literature has focused on using alpha power as the metric for measuring frontal brain asymmetry, as inverse alpha activity has been reliably demonstrated to predict approach-motivated behaviors (Hofman & Schutter, 2012). However, a study conducted by Schutter et al. (2008) suggested that activity in the beta band may play a role in motivation-related behaviors as well. Increased beta activity has been found to be associated with enhanced GABAergic inhibition (Jensen et al., 2005), therefore it can be inferred that approach-avoidance motivational tendencies can be reflected by frontal beta asymmetry. Schutter and colleagues (2008) investigated this hypothesis and found that self-reported approach and avoidance tendencies were related to frontal beta asymmetry. More specifically, higher approach-to-avoidance tendencies were correlated with reduced left-to-right sided beta asymmetries due to the inhibitory nature associated with beta activity in the right hemisphere. The greater amount of beta activity in the right hemisphere compared to the left hemisphere resulted in higher activation of the left hemisphere, which was associated with increased approach-motivated tendencies (as previously demonstrated). These findings provide a promising avenue of future research in which specific approach-motivated behaviors that result in engagement, such as curiosity, have the potential to be measured objectively using frontal asymmetry with beta power.

**Current Study**

The current study aimed to provide further support for the relationship between curiosity and learning. I hypothesized that both curiosity ratings and information prediction error values would be significantly correlated with recall rates, such that higher curiosity ratings and higher information prediction error values would be associated with higher recall rates.

However, the main goal of the current study was to expand the curiosity literature by determining whether an objective measure of a state of curiosity could be obtained through the use of EEG methods. Frontal brain asymmetry (using both alpha and beta power) and several other measures of EEG frequency components (e.g., relative percentages of activity in the delta, theta, alpha, and beta bands and the average theta/beta ratio) served as physiological indices that have the potential to evaluate a brain state of curiosity. Based on prior research, it was expected that brain activity using a variety of EEG metrics may look different when individuals are processing items that they are curious about compared to items that they are not curious about.

I hypothesized that the relative percentage of activity in the beta band will be positively correlated with curiosity ratings. Second, I hypothesized that the average theta/beta ratio will be inversely related to ratings of curiosity, such that greater ratios will be associated with lower ratings of curiosity. Third, I hypothesized that there will be higher activation in the left frontal cortex (greater frontal brain asymmetry) with both higher ratings of curiosity and higher recall rates. The remaining measures of EEG frequency components (e.g., relative percentage of activity in the delta, theta, and alpha bands) do not have consistent or well-defined relationships with curiosity-related states; therefore, these analyses were exploratory.

## Method

### Participants

A total of 22 Radford University undergraduate students participated in this study and were awarded extra credit for participation. However, three participants were excluded from EEG analyses due to insufficient electrode impedance levels or issues with the recording software, leading to a total of 19 participants with both EEG and behavioral data. Participants' ages ranged from 18 to 39 years old ($M$ = 22.27, $SD$ = 4.66). Of the 22 participants, 14 identified as White, four identified as Black, and four identified with two or more ethnicities. A majority of participants in the study identified as female ($N$ = 17). The number of years of education that participants have completed ranged from 13 to 17 years ($M$ = 15.05, $SD$ = .95). Additionally, a majority of participants indicated they were right-handed ($N$ = 19). The typical number of hours of sleep participants get per night ranged from 4 to 10 hours ($M$ = 7.14, $SD$ = 1.52), and the amount of sleep participants received the night before completing the study ranged from 4 to 9 hours ($M$ = 6.96, $SD$ = 1.20).

**Design**

The study was a repeated-measures correlational design, in which all participants were presented with the same set of 30 general interest trivia items.

The study consisted of two main phases: a learning phase and a testing phase. The learning phase required responses of prior knowledge as well as confidence and curiosity ratings of the answers to each trivia question. Participants read each trivia question that was presented and were able to think about what the answer may be before it was revealed. This phase also asked for ratings of satisfaction and initial accuracy with the answers to each trivia question once they were revealed. EEG signals were obtained throughout the entirety of this phase, but analyses focused on brain activity that preceded the presentation of each answer, which should reflect anticipatory states of low or high curiosity. We also conducted analyses on EEG data that were obtained while participants were viewing the answer to each question, which provides insight into brain activity while learning is occurring. The testing phase measured how much participants learned from the trivia task and whether more answers were remembered when higher curiosity/satisfaction ratings were initially provided.

## Materials/Apparatus

### *Trivia Items*

Curiosity was measured using a trivia question paradigm in line with prior research. A total of 30 general interest trivia questions and answers were drawn from a standardized database (Fastrich et al., 2018). The trivia items and subsequent ratings were presented on the computer using the stimulus-presentation software program SuperLab 6.0. See Appendix A for a full list of trivia questions and answers that were used for the current study.

### *Demographics*

Information including age, gender, race/ethnicity, years of education, handedness, and sleep quantity was collected from each participant.

### *Recall Test*

A simple recall test was used to test participants' memory for the trivia items that they previously saw during the curiosity task, which acted as an indicator of learning. This recall test consisted of all 30 trivia questions printed on a sheet of paper in a question format, with a blank space provided for the answer. Participants were instructed to write down the answer to each question to the best of their ability.

### *EEG Equipment*

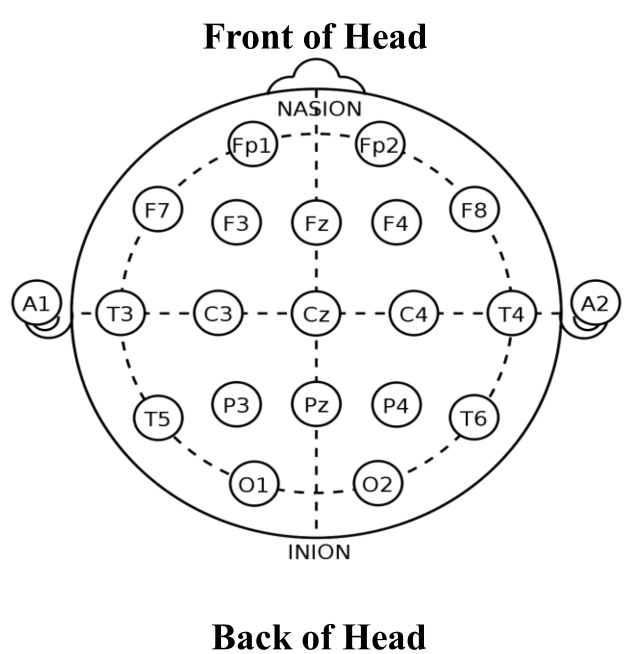
A 19-channel electrode cap was used for collection of electrical brain activity, and the Deymed Diagnostic TruScan EEG system was used to record the signals. Data were collected from all 19 electrode sites. Each electrode was wrapped in a small sponge that had been soaking in a solution of NaCl in order to reduce surface impedance. EEG data were amplified through a

TruScan LT headbox and interfaced with a Windows PC. The sampling rate of data was set to 200 voltages/second. All subsequent preprocessing and EEG data analyses were conducted using the TruScan Acquisition software. The location of each electrode on the scalp is displayed in Figure 3 below.

**Exclusions.** Several trials from multiple participants had to be excluded from analyses due to a failure of marker insertion into the EEG record to indicate appropriate waiting and answer periods. A total of 10 trials across five participants were removed from analysis, resulting in 560 usable trials out of a possible 570. Additionally, data from several electrodes were removed from analyses due to insufficient impedance levels during the recording. A total of 30 electrodes across six participants were removed, resulting in 331 usable electrode locations out of a possible 361. Based on prior EEG literature, the criterion for exclusion on the basis of insufficient impedance levels was any electrode that had a value greater than or equal to 20 KOhm.

**Figure 3**

*Position of Electrodes Across the Cortex*



**Procedure**

Participants were first given an informed consent agreement that had to be signed before participation. Next, participants were situated with the electrode cap and hooked up to the EEG system, with electrodes placed in all 19 sites, plus two additional sites for the ground and reference electrodes. Once successful impedance levels were obtained, one minute of EEG baseline was recorded—30 seconds with the participants' eyes open and 30 seconds with their eyes closed.

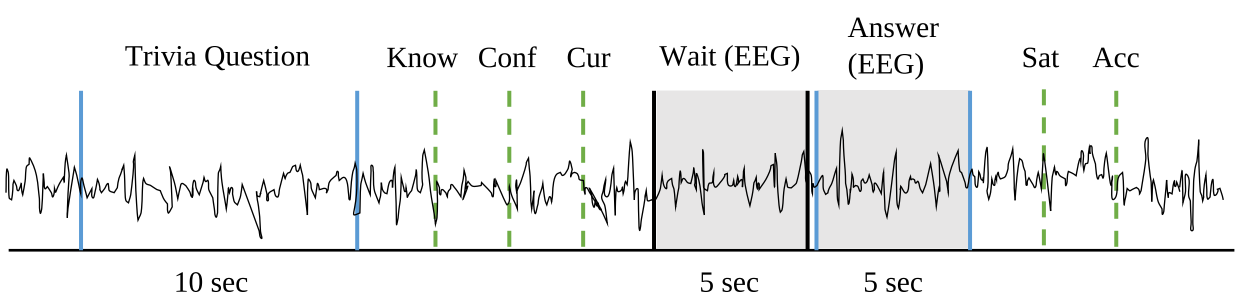
After the baseline recording, participants underwent the curiosity task while EEG was being continuously recorded. This was a within-subjects design in which all participants were presented with a set of 30 general interest trivia items (Fastrich et al., 2018) that appeared in a random order. Each trial consisted of the following: a trivia question, knowledge rating, confidence rating, curiosity rating, waiting period, trivia answer, satisfaction rating, and knowledge accuracy rating, in that order. Each trivia question was presented on the computer screen for a duration of 10 seconds. After seeing a trivia question, participants noted their prior knowledge by pressing "Y" on the keyboard if they believed they already knew the answer to the question or "N" if they either did not know the answer or were unsure. Participants then indicated their confidence in the answer on a scale from 1-100 (1 = *very unsure*, 100 = *very sure*) using the keyboard. Levels of curiosity about the answer to the trivia question were measured next using self-report on a 7-point numerical rating scale (1 = *not at all curious*, 7 = *very curious*). Next, participants initiated the placement of a marker in the EEG record by pressing the spacebar on the keyboard, which indicated the beginning of a 5-second waiting period. The answer to the trivia question was then provided and shown on the screen for 5 seconds. Participants then rated how satisfied they were with the answer they received using self-report on a 7-point numerical rating scale (1 = *not at all satisfied*, 7 = *very satisfied*). Next, participants made note of their original accuracy rating by selecting “Y” if they were accurate in knowing the correct answer beforehand or “N” if they were not. The curiosity task was completed once participants cycled through all 30 trials. At this point, the EEG recording was stopped, and participants were unhooked from the EEG system. The entire task took approximately 20 minutes to complete. Figure 4 below depicts the breakdown of a single trial of the curiosity task into individual components with relevant timescales.

After completion of the curiosity task, demographic information such as age, gender, race/ethnicity, years of education, handedness, and sleep quantity was collected. This questionnaire served as a buffer task between the learning and testing phase during which information in working memory was cleared.

Next, participants were instructed to complete a memory recall test, in which they wrote down the answer to each of the trivia questions that they had previously encountered to the best of their ability. Participants were then debriefed about the nature of the study and appropriately compensated for their time. The entire session took approximately one hour to complete.

**Figure 4**

*Breakdown of an Individual Trial in the Curiosity Task*




*Note*. This figure depicts the components and relevant timescales of a single trial in the curiosity task. The highlighted sections indicate those from which a segment of EEG data was obtained for analyses. Abbreviations are as follows: Know = knowledge rating, Conf = confidence rating, Cur = curiosity rating, Sat = satisfaction rating, and Acc = knowledge accuracy rating.

## Results

All analyses were conducted at the trial level in order to increase power and allow for detection of effects that may not have been revealed at the level of participant. Using the trial level of analysis, we ended up with $N$ = 660 behavioral cases (from 22 participants) and a maximum of $N$ = 560 cases with usable EEG data (from 19 participants). The number of cases for each EEG analysis was dependent upon the number of electrode locations that were excluded.

To try to account for variability from differences between participants, a multilevel model was run with trial as the level one variable and participant as the level two variable. The model indicated that there were significant individual differences in slopes and intercepts when EEG measures were predicting curiosity ratings. In order to remove the influence of variability associated with participant, numerical values for both behavioral and EEG measures were residualized by participant number. Participant number was dummy coded, whereby 21 dummy coded predictor variables were created to capture variability associated with the 22 levels of participant number. Each study variable was predicted from the set of 21 dummy coded variables, and residualized scores were retained for use in further analyses.

### Behavioral Analyses

#### *Calculation of Information Prediction Error*

Values representing an information prediction error were calculated using curiosity and satisfaction ratings. The curiosity rating for each trial was subtracted from the satisfaction rating for each trial (satisfaction – curiosity) to represent the difference between the actual value of the information received and the anticipated value of the information. For example, a curiosity rating of 2 and a satisfaction rating of 5 results in an information prediction error of +3, while a curiosity rating of 6 and a satisfaction rating of 4 results in an information prediction error of -2.

### ***Descriptive and Frequency Statistics***

Descriptive and frequency statistics for each behavioral measure were obtained. Participants indicated having prior knowledge of the answers to the trivia questions on 59.4% of trials (knowledge), and on 76.4% of trials, participants later indicated that they were incorrect in their initial judgment of the answer (accuracy). Values for confidence ranged from 0 to 100 ($M$ = 36.18, $SD$ = 32.82), and the standard deviation indicates there was a large amount of variability in how confident participants were in knowing the answers before they were shown. The mean curiosity rating was 5.69 ($SD$ = 1.73), with a rating of 7 occurring in 50.6% of trials. The mean satisfaction rating was 5.43 ($SD$ = 1.91), with a rating of 7 occurring in 46.1% of trials. The large number of curiosity and satisfaction ratings that are piled at the top of the scale indicates the presence of negatively skewed distributions. Values for information prediction error ranged from -6 to +11 ($M$ = -.26, $SD$ = 1.61). Learning, as measured by whether participants answered trivia questions correctly during the recall test, occurred on 89.2% of trials, which suggests that recall performance was near ceiling.

### ***Correlational Analyses***

Due to the highly skewed distribution of curiosity and satisfaction ratings, nonparametric tests of correlation were used to determine the strength of the relationships between all pairwise combinations of the behavioral variables. A Spearman’s rank-order correlation coefficient was obtained for each combination to determine whether there was a statistically significant correlation between the rank orderings for each pair of variables. I hypothesized that both curiosity ratings and information prediction error values would be significantly correlated with recall rates, such that higher curiosity ratings and higher information prediction values would be associated with higher recall rates. However, results did not support this hypothesis. There was no significant correlation between curiosity ratings and learning ($r_s$ = .049, $p$ = .212), nor between information prediction error and learning ($r_s$ = .055, $p$ = .156). In other words, there was no relationship between curiosity and accuracy on the recall test or between information prediction error and accuracy on the recall test. On the other hand, exploratory analyses revealed that there were significant correlations between prior knowledge and curiosity ($r_s$ = .134, $p$ < .001), meaning that when participants indicated they knew the answer beforehand, they were more curious to find out the correct answer. There was also a significant correlation between curiosity and confidence ($r_s$ = .151, $p$ < .001), such that higher ratings of confidence were associated with higher curiosity ratings. See Table 1 below for a complete list of all bivariate correlations between behavioral measures.

**Table 1**

*Correlations Between Behavioral Measures*

| | | **Knowledge** | **Confidence** | **Curiosity** | **Satisfaction** | **Accuracy** | **Pred. Error** | **Learning** |
|---|---|---|---|---|---|---|---|---|
| **Knowledge** | $r_s$ | - | | | | | | |
| | *Sig.* | - | | | | | | |
| | *N* | - | | | | | | |
| **Confidence** | $r_s$ | .741** | - | | | | | |
| | *Sig.* | <.001 | - | | | | | |
| | *N* | 660 | - | | | | | |
| **Curiosity** | $r_s$ | .134** | .151** | - | | | | |
| | *Sig.* | <.001 | <.001 | - | | | | |
| | *N* | 660 | 660 | - | | | | |
| **Satisfaction** | $r_s$ | .084* | .124** | .335** | - | | | |
| | *Sig.* | .030 | .001 | <.001 | - | | | |
| | *N* | 660 | 660 | 660 | - | | | |
| **Accuracy** | $r_s$ | .341** | .329** | .052 | .230** | - | | |
| | *Sig.* | <.001 | <.001 | .181 | <.001 | - | | |
| | *N* | 660 | 660 | 660 | 660 | - | | |

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| **Pred. Error** | $r_s$ | -.050 | -.020 | -.366** | .646** | .179** | - | |
| | *Sig.* | .203 | .606 | <.001 | <.001 | <.001 | - | |
| | *N* | 660 | 660 | 660 | 660 | 660 | - | |
| **Learning** | $r_s$ | .106** | .040 | .049 | .073 | .117** | .055 | - |
| | *Sig.* | .006 | .311 | .212 | .061 | .003 | .156 | - |
| | *N* | 660 | 660 | 660 | 660 | 660 | 660 | - |

**Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

## EEG Analyses

Overall, our goal for this set of analyses was to assess the strength of the relationship between 1) EEG activity in different electrode locations and in different frequency bands and 2) behavioral measures.

### *Identification of EEG Segments*

Data from the EEG recordings were obtained from two periods within each trial: the 5-second window that occurred while participants were waiting to see the answer to a question (curiosity phase) and the 5-second window that occurred while participants were viewing the correct answer (learning phase). During these periods, EEG segments of at least 0.5 – 3 seconds were identified. The length of the segments obtained during those windows was that of the longest segment over which no artifacts (e.g., eyeblinks or other muscle/amplifier artifacts) in the EEG record were present. The longest segments available in each trial were used for analysis.

### *Spectral Analysis of EEG Segments*

Deymed’s TruScan Explorer Software was used to perform spectral analysis on identified EEG segments corresponding to each trivia question. A Fast Fourier Transform algorithm was used to calculate the spectral power (variance) associated with each frequency that falls within the range of 0.5 – 40 Hz. The power values assigned to each frequency represent the degree to which each frequency is present in the EEG signal. The pattern of frequencies was reduced further by summing values for spectral density within frequencies assigned to four frequency bands: delta (0.5 – 3 Hz), theta (3 – 8 Hz), alpha (8 – 12 Hz), beta (12 – 40 Hz) (see Figure 1). The software reported the relative percentage of EEG activity that occurred within each of the four frequency bands (representing the percentage of area under the spectral density curve). These percentages were reported for each of the 19 electrode locations.

### ***Measures Extracted for Each EEG Segment***

The following measures were obtained from each EEG segment: raw percentage of activity in the delta, theta, alpha, and beta bands; the theta/beta ratio (the percentage of activity in the theta band divided by the percentage of activity in the beta band); the natural log of the ratio of beta activity in the F4 electrode site to beta activity in the F3 electrode site (measuring frontal beta asymmetry); and the natural log of the ratio of alpha activity in the F4 electrode site to alpha activity in the F3 electrode site (measuring frontal alpha asymmetry).

### ***Multilevel Modeling***

Separate multilevel models were fit to the data for regression equations predicting ratings of curiosity from values for beta power in the key electrode sites of F3, F4, C3, and C4. When the percentage of power in the beta band recorded at electrode location C3 was used to predict curiosity ratings, a random slopes and intercepts model provided a significantly better fit to the data than a random intercepts model, $X^2(2, N = 660) = 177.38, p < .001$. Comparable effects in terms of size and significant levels were observed when percentages of beta power obtained from the C4, F3, and F4 electrode locations were used as predictor variables. This indicates that these regression equations vary significantly across participants, hence the need to create residualized scores for study variables that remove variability associated with the participant from which trial-level data were obtained. These results imply that these relationships are not occurring simply as a function of having trials nested within participants. Instead, the strength of the correlations is dependent upon which participant's data is being analyzed.

### *Correlational Analyses*

**EEG Measures During the Curiosity Phase.** To determine whether there was a relationship between EEG activity before participants saw the correct answer and curiosity ratings, several correlational analyses were conducted. It was hypothesized that the theta/beta ratio would be inversely related to ratings of curiosity, such that greater ratios would be associated with lower ratings of curiosity. Results using Spearman's rank-order correlation indicated that there were no significant correlations between values for theta/beta ratio and curiosity ratings at any electrode locations (correlation coefficients ranged from $r_s = -.083$ to $r_s = .035$). It was also hypothesized that there would be higher activation in the left frontal cortex (greater frontal brain asymmetry) with higher ratings of curiosity. However, results showed that there was no significant correlation between frontal brain asymmetry and curiosity ratings in either the alpha ($r_s = -.024$, $p = .576$) or beta band ($r_s = -.011$, $p = .800$).

Finally, it was hypothesized that the relative percentage of activity in the beta band would be positively correlated with curiosity ratings. Results supported this hypothesis, with correlations ranging from $r_s = .018$ ($p = .695$) at electrode T6 to $r_s = .127$ ($p = .003$) at electrode C3. This indicates that more activity in the beta band was present during trials when curiosity ratings were higher. The strongest correlations between beta activity and curiosity ratings occurred in the frontal and central electrode regions, with correlations becoming weaker the farther back on the cortex the electrodes were located. Additionally, exploratory analyses showed that similar results were found in the delta band, but in the opposite direction. Results showed consistent negative correlations between delta activity and curiosity ratings, with correlations ranging from $r_s$ = -.014 ($p$ = .760) at electrode P3 to $r_s$ = -.128 ($p$ = .002) at electrode F7. This indicates that less activity in the delta band was present during trials when curiosity ratings were higher. Like the pattern of beta correlations, the strongest correlations between activity in the delta band and curiosity ratings occurred in the frontal and central electrode regions, with correlations becoming weaker the farther back on the cortex the electrodes were located. Further exploratory analyses showed no significant correlations between activity in either the theta or alpha bands with curiosity ratings.

The following tables display results of the bivariate correlations between behavioral measures and relative EEG values in the delta, theta, alpha, and beta bands during the curiosity phase, separated by electrode region: Table 2 – frontal electrodes, Table 3 – central electrodes, Table 4 – temporal electrodes, Table 5 – parietal electrodes, and Table 6 – occipital electrodes.

**Table 2**

*Correlations Between EEG Frontal Electrode Curiosity Segments and Behavioral Measures*

| | | **Knowledge** | **Confidence** | **Curiosity** | **Satisfaction** | **Accuracy** | **Pred. Error** | **Learning** |
|---|---|---|---|---|---|---|---|---|
| **Fp1 - D** | $r_s$ | -.105$^{*}$ | -.127$^{**}$ | -.100$^{*}$ | -.109$^{**}$ | -.063 | -.054 | -.038 |
| | *Sig* | .013 | .003 | .017 | .010 | .138 | .201 | .364 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fp1 - T** | $r_s$ | -.035 | .010 | -.047 | .010 | -.010 | .047 | .023 |
| | *Sig* | .403 | .818 | .264 | .822 | .821 | .271 | .581 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fp1 - A** | $r_s$ | .057 | .115$^{**}$ | .073 | .102$^{*}$ | -.020 | .066 | .037 |
| | *Sig* | .181 | .007 | .085 | .016 | .639 | .120 | .388 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fp1 - B** | $r_s$ | .111$^{**}$ | .089$^{*}$ | .093$^{*}$ | .038 | .107$^{*}$ | -.023 | .027 |
| | *Sig* | .008 | .035 | .027 | .364 | .012 | .588 | .524 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fp2 - D** | $r_s$ | -.142$^{**}$ | -.161$^{**}$ | -.115$^{**}$ | -.134$^{**}$ | -.035 | -.041 | -.038 |
| | *Sig* | .001 | <.001 | .008 | .002 | .418 | .348 | .381 |

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |
| **Fp2 - T** | $r_s$ | -.030 | .008 | -.036 | .000 | -.054 | .023 | .036 |
| | *Sig* | .485 | .862 | .412 | .999 | .214 | .595 | .405 |
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |
| **Fp2 - A** | $r_s$ | .090* | .161** | .098* | .135** | -.018 | .058 | .031 |
| | *Sig* | .038 | <.001 | .024 | .002 | .679 | .183 | .482 |
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |
| **Fp2 - B** | $r_s$ | .135** | .117** | .093* | .065 | .106* | -.012 | .032 |
| | *Sig* | .002 | .007 | .032 | .132 | .014 | .775 | .456 |
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |
| **F7 - D** | $r_s$ | -.111** | -.116** | -.128** | -.104* | .006 | -.011 | -.029 |
| | *Sig* | .009 | .006 | .002 | .014 | .880 | .794 | .490 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F7 - T** | $r_s$ | -.011 | -.025 | -.003 | .016 | -.067 | .000 | -.001 |
| | *Sig* | .790 | .562 | .951 | .711 | .113 | .992 | .978 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F7 - A** | $r_s$ | .042 | .109** | .099* | .099* | -.033 | .042 | .047 |
| | *Sig* | .318 | .010 | .019 | .019 | .432 | .320 | .272 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F7 - B** | $r_s$ | .091* | .091* | .086* | .058 | .044 | -.018 | .008 |
| | *Sig* | .031 | .031 | .042 | .169 | .296 | .664 | .846 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F3 - D** | $r_s$ | -.113** | -.127** | -.107* | -.117** | -.038 | -.050 | -.021 |
| | *Sig* | .008 | .003 | .012 | .006 | .367 | .240 | .628 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F3 - T** | $r_s$ | -.016 | .008 | -.013 | -.016 | -.028 | -.006 | -.064 |
| | *Sig* | .704 | .859 | .756 | .709 | .514 | .884 | .132 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F3 - A** | $r_s$ | .067 | .119** | .088* | .127** | .013 | .076 | .037 |
| | *Sig* | .111 | .005 | .037 | .003 | .762 | .072 | .384 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F3 - B** | $r_s$ | .113** | .098* | .114** | .060 | .076 | -.023 | .048 |
| | *Sig* | .008 | .021 | .007 | .153 | .074 | .587 | .256 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fz - D** | $r_s$ | -.121** | -.133** | -.118** | -.131** | -.019 | -.031 | .000 |
| | *Sig* | .004 | .002 | .005 | .002 | .649 | .461 | .998 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fz - T** | $r_s$ | .013 | .027 | .032 | -.005 | -.042 | -.038 | -.058 |
| | *Sig* | .767 | .524 | .455 | .905 | .320 | .370 | .173 |

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fz - A** | $r_s$ | .059 | .096* | .100* | .138** | -.005 | .060 | .013 |
| | *Sig* | .164 | .023 | .017 | .001 | .906 | .156 | .767 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Fz - B** | $r_s$ | .116** | .132** | .109* | .065 | .073 | -.026 | -.006 |
| | *Sig* | .006 | .002 | .010 | .126 | .086 | .543 | .897 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F4 - D** | $r_s$ | -.129** | -.139** | -.117** | -.090* | -.024 | -.009 | -.021 |
| | *Sig* | .002 | <.001 | .006 | .034 | .565 | .837 | .625 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F4 - T** | $r_s$ | -.028 | .001 | .022 | -.022 | -.032 | -.021 | -.047 |
| | *Sig* | .512 | .973 | .608 | .598 | .456 | .622 | .266 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F4 - A** | $r_s$ | .092* | .123** | .090* | .071 | -.005 | .020 | .026 |
| | *Sig* | .030 | .003 | .032 | .093 | .906 | .642 | .538 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F4 - B** | $r_s$ | .126** | .120** | .102* | .066 | .077 | -.026 | .035 |
| | *Sig* | .003 | .004 | .015 | .119 | .069 | .534 | .415 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **F8 - D** | $r_s$ | -.134** | -.161** | -.109* | -.078 | -.038 | -.017 | -.021 |
| | *Sig* | .002 | <.001 | .012 | .071 | .378 | .697 | .631 |
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |
| **F8 - T** | $r_s$ | -.040 | -.036 | -.009 | -.018 | -.047 | .010 | -.039 |
| | *Sig* | .359 | .414 | .845 | .679 | .285 | .819 | .372 |
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |
| **F8 - A** | $r_s$ | .100* | .144** | .110* | .113** | .024 | .043 | .033 |
| | *Sig* | .021 | <.001 | .011 | .009 | .576 | .325 | .444 |
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |
| **F8 - B** | $r_s$ | .164** | .161** | .080 | .055 | .075 | -.014 | .023 |
| | *Sig* | <.001 | <.001 | .065 | .208 | .085 | .756 | .599 |
| | *N* | 531 | 531 | 531 | 531 | 531 | 531 | 531 |

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

**Table 3**

*Correlations Between EEG Central Electrode Curiosity Segments and Behavioral Measures*

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| **C3 - D** | $r_s$ | -.073 | -.092* | -.086* | -.082 | .014 | -.025 | -.021 |
| | *Sig.* | .083 | .030 | .041 | .051 | .739 | .555 | .627 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **C3 - T** | $r_s$ | -.014 | -.059 | -.007 | -.010 | -.073 | -.028 | -.031 |
| | *Sig.* | .732 | .161 | .873 | .806 | .084 | .507 | .468 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **C3 - A** | $r_s$ | .050 | .106* | .031 | .055 | -.005 | .035 | .017 |
| | *Sig.* | .241 | .012 | .466 | .194 | .906 | .411 | .682 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **C3 - B** | $r_s$ | .068 | .097* | .127** | .054 | .032 | -.022 | .009 |
| | *Sig.* | .106 | .021 | .003 | .199 | .451 | .602 | .826 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Cz - D** | $r_s$ | -.070 | -.074 | -.089* | -.075 | .027 | -.009 | -.017 |
| | *Sig.* | .098 | .080 | .036 | .076 | .530 | .825 | .686 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Cz - T** | $r_s$ | -.075 | -.070 | .043 | .009 | -.046 | -.042 | .016 |
| | *Sig.* | .074 | .100 | .312 | .830 | .279 | .320 | .697 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Cz - A** | $r_s$ | .045 | .064 | .056 | .090* | .024 | .053 | .038 |
| | *Sig.* | .288 | .129 | .184 | .034 | .575 | .208 | .367 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **Cz - B** | $r_s$ | .114** | .134** | .086* | .018 | .038 | -.020 | -.005 |
| | *Sig.* | .007 | .002 | .042 | .674 | .368 | .631 | .914 |
| | *N* | 560 | 560 | 560 | 560 | 560 | 560 | 560 |
| **C4 - D** | $r_s$ | -.086* | -.108* | -.077 | -.060 | -.016 | .002 | -.012 |
| | *Sig.* | .047 | .013 | .078 | .167 | .705 | .964 | .782 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |
| **C4 - T** | $r_s$ | -.058 | -.028 | -.059 | -.046 | -.040 | .025 | .012 |
| | *Sig.* | .184 | .520 | .175 | .292 | .364 | .564 | .775 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |
| **C4 - A** | $r_s$ | .059 | .088* | .076 | .076 | .038 | .017 | -.001 |
| | *Sig.* | .177 | .043 | .081 | .081 | .386 | .701 | .990 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |
| **C4 - B** | $r_s$ | .078 | .074 | .099* | .028 | .015 | -.048 | -.012 |
| | *Sig.* | .072 | .089 | .023 | .520 | .723 | .270 | .786 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

**Table 4**

*Correlations Between EEG Temporal Electrode Curiosity Segments and Behavioral Measures*

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| **T3 - D** | $r_s$ | -.027 | -.051 | -.097* | -.014 | .033 | .050 | .016 |
| | *Sig.* | .539 | .245 | .025 | .746 | .442 | .249 | .711 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |
| **T3 - T** | $r_s$ | -.029 | -.080 | -.030 | .032 | .039 | .037 | .011 |
| | *Sig.* | .511 | .067 | .486 | .465 | .372 | .400 | .804 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |
| **T3 - A** | $r_s$ | .014 | .071 | .043 | .013 | -.004 | .001 | .044 |
| | *Sig.* | .744 | .105 | .328 | .773 | .926 | .989 | .313 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |
| **T3 - B** | $r_s$ | .036 | .054 | .120** | .036 | -.052 | -.050 | -.074 |
| | *Sig.* | .402 | .217 | .006 | .414 | .228 | .254 | .088 |
| | *N* | 530 | 530 | 530 | 530 | 530 | 530 | 530 |
| **T4 - D** | $r_s$ | -.048 | -.091* | -.100* | -.007 | -.011 | .036 | .052 |
| | *Sig.* | .281 | .043 | .025 | .878 | .806 | .428 | .243 |
| | *N* | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| **T4 - T** | $r_s$ | -.057 | -.047 | -.004 | .010 | .004 | .017 | .007 |
| | *Sig.* | .206 | .294 | .929 | .828 | .929 | .712 | .877 |
| | *N* | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| **T4 - A** | $r_s$ | .012 | .041 | .099* | .045 | -.007 | -.011 | .012 |
| | *Sig.* | .788 | .358 | .027 | .315 | .878 | .807 | .790 |
| | *N* | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| **T4 - B** | $r_s$ | .067 | .112* | .046 | -.016 | .027 | -.039 | -.083 |
| | *Sig.* | .133 | .012 | .302 | .724 | .547 | .389 | .063 |
| | *N* | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| **T5 - D** | $r_s$ | .014 | .028 | -.020 | -.037 | .022 | -.053 | -.039 |
| | *Sig.* | .763 | .557 | .673 | .443 | .650 | .266 | .418 |
| | *N* | 441 | 441 | 441 | 441 | 441 | 441 | 441 |
| **T5 - T** | $r_s$ | -.106* | -.075 | .003 | .025 | -.013 | .017 | -.013 |
| | *Sig.* | .026 | .118 | .945 | .595 | .778 | .720 | .783 |
| | *N* | 441 | 441 | 441 | 441 | 441 | 441 | 441 |
| **T5 - A** | $r_s$ | -.045 | -.060 | -.024 | -.010 | -.028 | .050 | .026 |
| | *Sig.* | .348 | .212 | .621 | .832 | .553 | .293 | .583 |

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| | *N* | 441 | 441 | 441 | 441 | 441 | 441 | 441 |
| **T5 - B** | $r_s$ | .104* | .055 | .036 | -.006 | -.004 | -.012 | .022 |
| | *Sig.* | .029 | .248 | .450 | .896 | .940 | .809 | .650 |
| | *N* | 441 | 441 | 441 | 441 | 441 | 441 | 441 |
| **T6 - D** | $r_s$ | .029 | -.020 | -.027 | -.006 | -.002 | -.023 | .056 |
| | *Sig.* | .524 | .659 | .565 | .889 | .969 | .618 | .225 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **T6 - T** | $r_s$ | -.031 | .028 | .072 | .070 | -.006 | .004 | -.055 |
| | *Sig.* | .503 | .540 | .121 | .127 | .889 | .926 | .232 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **T6 - A** | $r_s$ | -.042 | -.011 | .033 | .010 | -.027 | .011 | -.031 |
| | *Sig.* | .365 | .809 | .477 | .836 | .565 | .813 | .498 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **T6 - B** | $r_s$ | .022 | .005 | .018 | .004 | .046 | .019 | -.023 |
| | *Sig.* | .639 | .914 | .695 | .923 | .317 | .677 | .626 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

**Table 5**

*Correlations Between EEG Parietal Electrode Curiosity Segments and Behavioral Measures*

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| **P3 - D** | $r_s$ | .057 | .052 | -.014 | -.104* | .003 | -.119** | .006 |
| | *Sig.* | .214 | .260 | .760 | .024 | .950 | .010 | .904 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **P3 - T** | $r_s$ | -.122** | -.105* | .046 | .044 | -.019 | .011 | -.020 |
| | *Sig.* | .008 | .023 | .322 | .337 | .684 | .809 | .669 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **P3 - A** | $r_s$ | -.050 | -.101* | -.033 | .075 | -.047 | .114* | .007 |
| | *Sig.* | .279 | .028 | .479 | .104 | .308 | .013 | .879 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **P3 - B** | $r_s$ | .116* | .127** | .025 | .026 | .039 | .042 | -.001 |
| | *Sig.* | .011 | .006 | .587 | .577 | .404 | .363 | .991 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **Pz - D** | $r_s$ | -.053 | -.061 | -.069 | -.074 | -.023 | -.023 | -.044 |
| | *Sig.* | .239 | .176 | .121 | .099 | .613 | .602 | .322 |

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| | *N* | 501 | 501 | 501 | 501 | 501 | 501 | 501 |
| **Pz - T** | $r_s$ | -.045 | -.020 | .060 | .043 | -.030 | -.020 | -.018 |
| | *Sig.* | .316 | .649 | .178 | .331 | .508 | .658 | .682 |
| | *N* | 501 | 501 | 501 | 501 | 501 | 501 | 501 |
| **Pz - A** | $r_s$ | .068 | .071 | .069 | .074 | -.002 | .011 | .068 |
| | *Sig.* | .129 | .112 | .125 | .096 | .972 | .802 | .131 |
| | *N* | 501 | 501 | 501 | 501 | 501 | 501 | 501 |
| **Pz - B** | $r_s$ | .028 | .052 | .047 | .026 | .033 | .022 | .014 |
| | *Sig.* | .536 | .242 | .297 | .564 | .463 | .618 | .748 |
| | *N* | 501 | 501 | 501 | 501 | 501 | 501 | 501 |
| **P4 - D** | $r_s$ | .015 | -.039 | -.019 | -.053 | .012 | -.053 | .040 |
| | *Sig.* | .739 | .397 | .687 | .254 | .794 | .254 | .386 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **P4 - T** | $r_s$ | -.044 | .013 | -.004 | .046 | -.010 | .042 | -.061 |
| | *Sig.* | .345 | .776 | .934 | .322 | .825 | .359 | .184 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **P4 - A** | $r_s$ | .002 | .005 | -.004 | .070 | -.024 | .076 | .021 |
| | *Sig.* | .962 | .917 | .929 | .130 | .604 | .101 | .656 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |
| **P4 - B** | $r_s$ | -.036 | -.020 | .049 | .029 | -.005 | .012 | -.030 |
| | *Sig.* | .437 | .664 | .289 | .536 | .914 | .799 | .511 |
| | *N* | 471 | 471 | 471 | 471 | 471 | 471 | 471 |

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

**Table 6**

*Correlations Between EEG Occipital Electrode Curiosity Segments and Behavioral Measures*

| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| **O1 - D** | $r_s$ | -.057 | -.058 | -.048 | -.067 | -.036 | -.050 | -.088 |
| | *Sig.* | .228 | .225 | .307 | .154 | .453 | .296 | .062 |
| | *N* | 447 | 447 | 447 | 447 | 447 | 447 | 447 |
| **O1 - T** | $r_s$ | -.070 | -.079 | .023 | .009 | -.076 | -.023 | -.016 |
| | *Sig.* | .141 | .094 | .623 | .854 | .108 | .633 | .739 |
| | *N* | 447 | 447 | 447 | 447 | 447 | 447 | 447 |
| **O1 - A** | $r_s$ | .036 | .052 | .031 | .060 | .019 | .048 | .067 |
| | *Sig.* | .444 | .277 | .513 | .205 | .686 | .306 | .157 |
| | *N* | 447 | 447 | 447 | 447 | 447 | 447 | 447 |

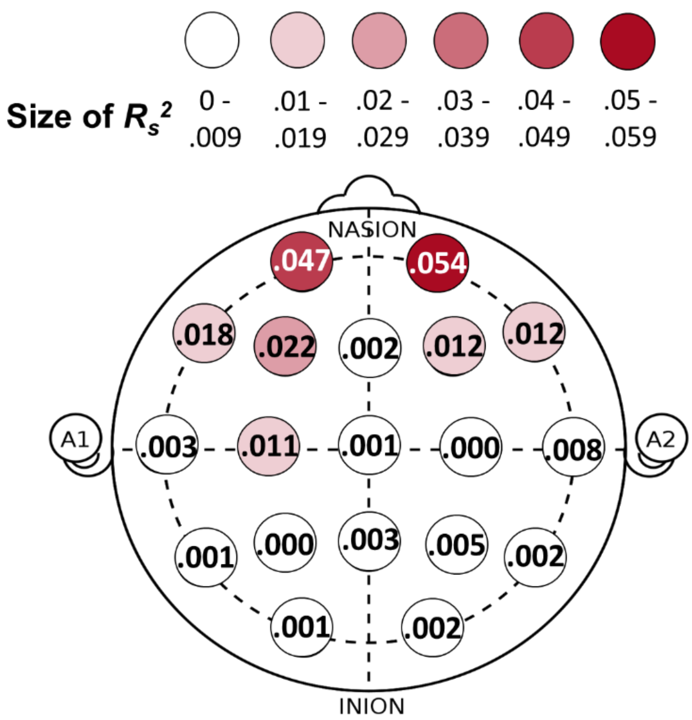
| | | Knowledge | Confidence | Curiosity | Satisfaction | Accuracy | Pred. Error | Learning |
|---|---|---|---|---|---|---|---|---|
| **O1 - B** | $r_s$ | .108* | .105* | .025 | .016 | .057 | .016 | .041 |
| | *Sig.* | .022 | .027 | .600 | .731 | .226 | .740 | .382 |
| | *N* | 447 | 447 | 447 | 447 | 447 | 447 | 447 |
| **O2 - D** | $r_s$ | -.027 | -.054 | -.032 | -.010 | -.002 | .001 | -.032 |
| | *Sig.* | .579 | .274 | .515 | .844 | .967 | .978 | .513 |
| | *N* | 417 | 417 | 417 | 417 | 417 | 417 | 417 |
| **O2 - T** | $r_s$ | -.054 | -.022 | .085 | .043 | .006 | -.022 | -.042 |
| | *Sig.* | .270 | .659 | .082 | .381 | .904 | .648 | .395 |
| | *N* | 417 | 417 | 417 | 417 | 417 | 417 | 417 |
| **O2 - A** | $r_s$ | .037 | .041 | -.012 | .007 | .001 | .019 | .020 |
| | *Sig.* | .457 | .400 | .813 | .891 | .979 | .696 | .685 |
| | *N* | 417 | 417 | 417 | 417 | 417 | 417 | 417 |
| **O2 - B** | $r_s$ | .037 | .052 | .028 | .006 | .003 | -.012 | .003 |
| | *Sig.* | .446 | .290 | .568 | .896 | .957 | .800 | .953 |
| | *N* | 417 | 417 | 417 | 417 | 417 | 417 | 417 |

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

**EEG Measures During the Learning Phase.** To determine whether there was a relationship between EEG activity while participants were viewing the correct answer and behavioral measures, several correlational analyses were conducted. Since this phase was added later in the study design process, all analyses involving EEG measures from this segment were exploratory and were not based on directional hypotheses. Results using Spearman's rank-order correlation again showed no significant correlations between frontal brain asymmetry in either the alpha or beta bands with any behavioral measures. There were also no significant correlations between theta/beta ratios and any of the behavioral measures during the learning phase. However, we did find significant correlations between relative activity in the beta band when participants were viewing the correct answer and curiosity ratings, particularly at frontal electrode sites. The strongest correlations between beta activity and curiosity ratings occurred at electrode sites Fp1 ($r_s$ = .120, $p$ = .004) and Fp2 ($r_s$ = .124, $p$ = .004). This indicates that the higher the curiosity ratings were, the higher the values for relative beta activity tended to be while participants were learning the correct answers. These correlations became even stronger when selecting for cases during which participants originally thought they knew the answer (e.g., indicated "yes" for prior knowledge), but were incorrect in their initial guess upon viewing the correct answer (e.g., indicated "no" for accuracy). In this condition, the correlations between beta activity and curiosity ratings at electrode site Fp1 was $r_s = .216$ ($p = .017$) and at electrode site Fp2 was $r_s = .232$ ($p = .013$). Figure 5 displays the squared correlations at each electrode location in the above condition.

**Figure 5**

*Squared Correlations Between Curiosity Ratings and Beta Activity During Learning*



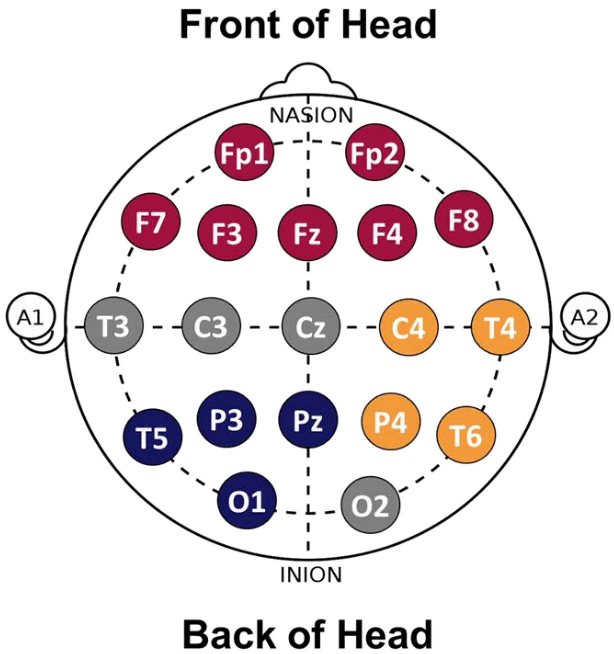

Analyses of EEG measures obtained during the learning phase also showed that there were consistent correlations between delta activity and curiosity ratings, with correlations ranging from $r_s$ = -.014 ($p$ = .756) at electrode Pz to $r_s$ = -.136 ($p$ = .001) at electrode Fp1. While participants were viewing the correct answer, higher curiosity ratings were associated with lower levels of delta activity. Similar to results obtained during the curiosity phase, there were no consistent correlations between relative activity in either the theta or alpha bands with behavioral measures during the learning phase.

***Exploratory Factor Analysis***

Principal component analysis was conducted to extract different factors of electrode groupings to determine which electrodes varied together in their activation patterns during the curiosity phase of the trivia task. A varimax rotation was performed with the values for relative beta activity that occurred at each of the 19 electrode sites. The initial round of factor analysis indicated that there were four factors, accounting for a total of 71.64% of the variance. Factor 1 had an eigenvalue of 9.18, which accounted for 48.31% of the variance, and consisted of all frontal electrodes (Fp1, Fp2, F7, F3, Fz, F4, and F8). Factor 2 had an eigenvalue of 2.30, accounting for 12.09% of the total variance. The electrodes that loaded on factor 2 included T5, P3, Pz, and O1, all of which are located towards the back of the left hemisphere. Factor 3 had an eigenvalue of 1.13 and accounted for 5.95% of the total variance. Electrodes C4, T4, P4, and T6 loaded onto factor 3 and represent areas of the mid-back right hemisphere. Finally, factor 4 had an eigenvalue of 1.01, which accounted for 5.29% of the variance. The electrodes that loaded onto factor 4 consisted of T3, C3, Cz, and O2; however, these electrodes loaded similarly onto other factors as well. See Figure 6 below for a depiction of electrode position and grouped activation by color.

**Figure 6**

*Grouped Activation of Electrodes by Factor*




*Note.* Electrodes in maroon comprise factor 1, electrodes in dark blue comprise factor 2, electrodes in orange comprise factor 3, and electrodes in gray comprise factor 4.

## Discussion

In order to determine whether an objective assessment of a brain state of curiosity could be characterized to increase measurement reliability, the current study examined if self-reported ratings of curiosity were related to several different metrics of EEG activity. Additionally, the current study sought to further investigate the relationships between curiosity, information prediction error, and learning. To examine these questions, we measured participants' curiosity about answers to trivia questions while recording EEG and then had them take a recall test on the trivia facts they had just learned. We did not find a significant relationship between curiosity and learning or between information prediction error and learning. There was also no significant correlation between curiosity and frontal brain asymmetry or between curiosity and relative theta/beta ratios. However, results showed that there were consistent correlations between curiosity and relative percentages of activity in both the beta (positive correlations) and delta (negative correlations) frequency bands obtained 1) before participants viewed the correct answer and 2) while participants were viewing the correct answer. These correlations occurred strongly at electrode sites that were located on both frontal and central regions of the cortex.

Exploratory analyses revealed that one condition in particular resulted in an even stronger relationship between beta activity recorded during learning and curiosity ratings: when participants initially thought they knew the answer to the question but realized they were wrong upon seeing the correct answer. The electrode sites Fp1 and Fp2, both located on the forehead, showed the strongest correlations between the above variables, which implicates the role of the prefrontal cortex in this condition. A further exploration of the EEG correlates of a curiosity state indicated that electrodes were categorized into four groupings, with each group representing a similar pattern of activation when participants were in the curiosity phase of the trial.

**Curiosity and Learning**

The findings of our first research question did not support our initial hypothesis of a relationship between curiosity and learning. Both curiosity ratings and memory performance were influenced by a negatively skewed distribution, so it is possible that there was not enough variability in scores to see a relationship emerge. However, this finding is also not entirely unprecedented; there have been mixed results in the literature regarding whether increased curiosity is related to learning. Some studies have found a positive relationship between curiosity and learning (e.g., Gruber et al., 2014; Marvin & Shohamy, 2016), yet others have found no relationship between these two variables (e.g., Arnold & Marsh, in prep; Chen et al., under review). These mixed results could be indicative of another factor either in addition to or instead of curiosity that is driving its relationship with learning.

One possibility is metacognitive abilities that increase learners' awareness of a knowledge gap, such as confidence and prior knowledge. For example, Chen and colleagues (under review) found that metacognition was associated with better learning outcomes, and that this memory enhancement occurred independent of curiosity. However, subjective prior knowledge estimates and confidence have been shown to provoke curiosity, especially while individuals are in a "*Feeling-of-Knowing*" state or region of proximal learning (Metcalfe et al., 2020). When individuals think they are close to knowing the answer, they are more likely to be motivated to find out what that answer is, leading to increased curiosity-based attentional processes. Similar to these results, exploratory analyses conducted in the current study revealed that when participants estimated they had some degree of prior knowledge of the answer, they were more likely to have higher ratings of curiosity. Furthermore, higher ratings of confidence were associated with higher ratings of curiosity, indicating a desire to confirm one's predictions (Wade & Kidd, 2019). While we cannot draw conclusions from the current study to implicate the roles of metacognitive abilities in driving the relationship between curiosity and learning, further research should be conducted to explore this possibility.

Contrary to results found by Marvin and Shohamy (2016), information prediction error did not correlate with subsequent learning in the current study. It was expected that people would better remember information for which there was a more-positive prediction error—when the value of received information exceeded the value of expected information. Predictions about the ability of information to resolve uncertainty should drive curiosity to close the information gap, therefore signaling importance to remember that information in the future (Loewenstein, 1994).

Because information prediction error was calculated using curiosity and satisfaction ratings, it is again possible that the expected relationship did not occur due to the skewed curiosity ratings and near-ceiling recall performance. A question asking, “How curious you are to find out the answer?” is self-explanatory; however, a question asking, “How satisfied are you with the answer?” is more ambiguous and may be interpreted in different ways. Participants may have had difficulty understanding exactly what was meant by satisfaction because it is a question that is not well-defined. Instead, there may be more effective ways to capture what is meant by the value of received information. For example, other studies have investigated the post-answer aspect of information prediction error by asking participants to rate how interesting the answer is (e.g., Fandakova & Gruber, 2021). Hence, more research is needed to confidently state whether information prediction error can be accurately conceptualized using curiosity and satisfaction ratings and whether it affects the relationship between curiosity and learning.

**EEG Correlates of Curiosity and Learning**

Due to studies that have shown that a decreased ratio of theta activity (slow wave) to beta activity (fast wave) is associated with heightened cognitive control (van Son et al., 2019), it was hypothesized that theta/beta ratios would be inversely related to ratings of curiosity. Conversely, the current study did not find a relationship between theta/beta ratios and curiosity ratings. Of notable importance is that a majority of previous studies obtained a resting state theta/beta ratio, which measures neural activity that occurs when individuals are not engaged in an explicit task. Resting state EEG can provide insight into endogenous neural activity that reflects individual differences in cognition and behavioral predispositions, such as attentional control and approach motivation (Massar et al., 2014). The current study instead obtained measures of theta/beta ratios while participants were engaged in the curiosity task (known as task-related EEG), which may be one reason for the opposing results that were found. Since the current study is more focused on investigating curiosity as a state rather than a trait, other EEG metrics may be more relevant in determining how curiosity can be objectively characterized. Future studies that are interested in studying correlates of trait curiosity may consider obtaining theta/beta ratios during resting state and comparing them to self-reported curiosity measures.

Using the information-as-reward approach, it was predicted that established measures of engagement and motivation, such as frontal brain asymmetry, would produce a more reliable measure of curiosity. It was expected that there would be higher neural activity in the left frontal cortex compared to the right when individuals were in a state of curiosity, and that this asymmetry would predict learning. However, results from the current study did not support this hypothesis; instead, frontal brain asymmetry was not associated with curiosity ratings or learning outcomes. Lima and Rocha (2019) obtained partially similar results: They did not find a relationship between frontal brain asymmetry and curiosity, but they did find that frontal brain asymmetry was able to predict learning. In other words, participants' recall was better for trials in which they showed greater asymmetry scores. It may be the case that frontal brain asymmetry is not a neural correlate of curiosity specifically but instead an indicator of overall motivation to learn. It is possible that if scores on the recall test were not at ceiling, the current study would have indeed found that greater frontal brain asymmetry would predict learning. However, we are not able to determine from the current study whether relationships between frontal brain asymmetry and curiosity and learning exist.

We expected that higher frequency brain waves (beta) would be present to a greater degree when individuals were in a heightened state of curiosity. Consistent with our hypothesis, the current study did find a relationship between the relative percentage of beta activity and curiosity ratings. Additionally, decreased activity in the delta band was associated with higher curiosity ratings, which represents an inverse relationship due to the slow-wave nature of delta activity. These relationships occurred both when EEG activity was obtained 1) before the correct answer was revealed to participants and 2) while participants were viewing the correct answer. In other words, there was an increase in beta activity when participants were more curious about finding out the answers. These results further support the findings that higher frequency brain waves are associated with states of concentration (Smith et al., 2003) because curiosity results in increased attentional processes (Gottlieb et al., 2013). Importantly, this key finding implies that neural correlates of curiosity can be measured—a brain state of curiosity can be characterized physiologically by the presence of beta waves. These correlates provide researchers with a potential objective measure of curiosity that, when used alongside self-report measures, can increase the consistency of measurement compared to relying on self-report alone. While these neural correlates are not able to provide information related to magnitude of curiosity, they can indicate when an individual is in a state of curiosity or not. With this knowledge, further research can begin to investigate other cognitive states that are also associated with increased beta waves to determine whether they influence the relationship between curiosity and learning.

Furthermore, when participants initially thought they knew the answer to the question but realized they were wrong upon seeing the correct answer, the relationship between beta activity and curiosity ratings became even stronger. Higher curiosity ratings were associated with increased beta activity while participants viewed the correct answer. Because the EEG activity that was measured in this condition occurred while participants were viewing the correct answer, it is assumed that they were in the process of learning that information. Participants' initial judgment error may have led to increased information processing due to memory updating.

The more curious an individual is, the stronger their drive will be to find out the answer and fill their knowledge gap. If an individual's initial prediction of the answer is incorrect and they were highly curious about it, they will likely put more effort into encoding and updating the new information because it is viewed as valuable in guiding future behavior. Additionally, the electrode sites Fp1 and Fp2 (located on the forehead) showed the strongest correlations in the above condition, which indicates increased activation of the prefrontal cortex region. This activation pattern is consistent with research that has shown that the prefrontal cortex is involved in maintaining and updating internal representations and executing functions related to information processing (Postle, 2006). This further supports the notion that the increased strength of the relationship between curiosity and beta activity found in the current study may have been due to memory updating.

Finally, a spatial distribution of EEG across the cortex showed that electrodes were categorized into four factors, with each factor representing a similar pattern of activation when participants were in the curiosity phase of the trial. Of particular note is the factor that encompasses all of the frontal lobe electrodes. This indicates that each of the electrodes in this region were varying in synchronous fashion with each other and displaying similar frequency patterns. These results reveal relevant dimensions of the pattern of electrical brain activity that can also be used to further characterize an objective brain state of curiosity. One future direction of research may be to examine correlates between behavioral measures and factor scores associated with these regions.

## Limitations and Future Directions

The present study comes with a few limitations in its method and interpretation. As mentioned previously, curiosity ratings were highly skewed in a negative direction, such that scores were clustered near the top of the scale. This may have been the case because participants were just truly that curious about all the trivia questions, especially since they were designed to be curiosity-inducing. Another potential reason for the skewed curiosity scores is due to demand characteristics—participants may have been responding with high levels of curiosity because that is how they thought they should respond based on the nature of the study. Future studies investigating curiosity and learning should consider either including trivia questions ranging from low to high curiosity-inducing or utilizing stimuli other than trivia questions to induce curiosity. Additionally, participants performed near-ceiling on the recall test, meaning that an overwhelming majority of questions were answered correctly. Therefore, we were not able to accurately assess whether other behavioral measures or EEG measures were related to learning due to reduced variability in scores. It is likely that the study design did not incorporate a long enough delay between the presentation of trivia answers and testing for forgetting to occur. To improve upon the current design, future studies should include a longer delay before testing or a more cognitively demanding interference task. Furthermore, the 19-channel EEG cap that was used for data collection was rudimentary compared to some of the other more extensive systems that are available for use. The design and functionality of the EEG cap was also limited in that it prevented the collection of usable data from individuals with thick hair, predominately those with Black/African American ethnicities. Based on these exclusions, the results may not be as generalizable to individuals of all backgrounds. Future work should aim to collect data using more sophisticated EEG equipment that includes a larger number of recording electrodes and the ability to obtain measures from a more diverse population. Finally, because this was a correlational design, we are not able to determine causality from any of our results; instead, we can only examine whether relationships between variables exist or not. Future research should focus on manipulating curiosity to investigate whether there is a causal effect of curiosity on both learning and EEG correlates.

## Conclusion

In summary, the current study provides an initial, but promising, framework for future studies to increase the reliability of curiosity measurements. By using a combination of EEG metrics, such as beta activity, and self-report, researchers can be more confident that they are assessing the construct of curiosity. Behaviors that have similar psychological properties to curiosity may be more accurately characterized by similar neural correlates, which can improve measurement consistency in other areas as well. While the relationship between curiosity and learning is still unclear, further broadening our understanding of this relationship could provide important insights for applied settings. Since curiosity plays a key role in impacting day to day behaviors, numerous fields such as education, marketing, and healthcare could benefit from this knowledge to improve learning strategies and related outcomes.

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## Appendix A

Trivia Items

1. What wild animal in Africa has killed the most people? *Hippo*

2. What is the name of the largest desert on earth? *Antarctica*

3. What spice is extremely poisonous if injected intravenously? *Nutmeg*

4. What animal can eat only when its head is upside down? *Flamingo*

5. What is the only food that never spoils? *Honey*

6. What taste are cats unable to detect? *Sweet*

7. What is the only internal human organ capable of natural regeneration of lost tissue? *Liver*

8. Scooby Doo is based on what breed of dog? *Great Dane*

9. What was the surname of the first president to appear on a U.S. coin? *Lincoln*

10. What was the world's first National Park? *Yellowstone*

11. What disability did Thomas Edison suffer from? *Deafness*

12. In which country is Angel Falls, the tallest waterfall, located? *Venezuela*

13. What color are cranberries before they turn red? *White*

14. Which country has the longest coastline? *Canada*

15. What was the first nation to give women the right to vote? *New Zealand*

16. Which sport uses the terms "stones" and "brooms"? *Curling*

17. Where in the body are male lobsters' bladders located? *Head*

18. What reptile, according to ancient legend, was able to live in fire? *Salamander*

19. Which city is the only one in the world to be situated in two continents? *Istanbul*

20. Which animal tastes with its feet? *Butterfly*

21. What American State has the highest percentage of people who walk to work? *Alaska*

22. What is the fastest healing body part on a human? *Tongue*

23. What is the name of the company that produces "Baby Ruth" candy bars? *Nestle*

24. What country is coffee originally from? *Ethiopia*

25. Which planet in our solar system was the last to be discovered? *Neptune*

26. What is the most common blood type in humans? *O positive*

27. What does the Scoville scale of food measure? *Spicy Heat*
28. What language has the largest vocabulary? *English*
29. What food did the Aztecs reckon was the food of the Gods? *Chocolate*
30. What is the only country to have won at least one gold in every Olympic Games? *Great Britain*